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Graduate Submission

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HUMAN-AI COGNITIVE INTERACTION IN MANUFACTURING INDUSTRY

Exploring the implementation of cognitive interaction to increase industry metrics

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Abstract

The world is witnessing a rapid transformation in the field of automation, with robots and Artificial Intelligence (AI) working with humans. While this development brings several advantages, it also poses significant challenges that need to be addressed. Communication, Task Allocation, Limited Sensory Capabilities, Rigid Actions of Robots, Transparency between Humans and Robots are the major challenging issues that industries are facing in present times. Traditionally, physical interaction between humans and robots involves a considerable amount of time and cost. It requires several training sessions to learn the intricacies of the interaction process for both humans and robots as well. This approach becomes even more challenging in a chain industrial environment, where reaching out to the exact human operators is difficult. This communication gap can lead to delayed operations and even hazardous incidents. As consultants in a high-tech, global manufacturing enterprise, we firmly support emphasizing Human-AI Interaction cognitively. With the innovation of neuroscience, there is a unique opportunity to establish a cognitive environment that combines the brain waves of humans and signals from robots. This approach offers several advantages, including saving time and improving productivity, while also creating a safer working environment for employees. By focusing on neurocognition science, our company can lead the way in developing innovative and effective solutions for Human-AI Interaction. Our company's exposure to this future technology will enable us to establish ourselves as thought leaders in the industry, paving the way for a brighter and more sustainable future.

1. Introduction

Human-AI cognitive interaction, with a particular emphasis on Brain-Computer Interface (BCI) technology, has evolved as a promising and transformative approach in various industrial domains. BCI enables direct communication and collaboration between the human brain and artificial intelligence systems, facilitating seamless information exchange and enhancing cognitive capabilities [1]. This integration of human intelligence and AI algorithms holds significant potential for revolutionizing industrial processes, enhancing productivity, and optimizing human-machine collaboration. This essay will examine the concept of human-AI cognitive interaction in the context of BCI and its implications for industry, drawing upon relevant research and literature to highlight the significance and potential applications in manufacturing industry settings.

1.1 Human and Artificial Intelligence

Human intelligence, as recognized as innate, biological intelligence, and artificial intelligence (AI), commonly referred to as machine intelligence, have been prominent issues in a broad range of scientific literature. Advances and even achievements in AI have typically demonstrated systems are capable of performing a variety of tasks and problems, including playing games like Go and Jeopardy and even producing art, such as music or paintings, or performing classification, ranking, and prediction tasks. In order to address dynamically changing and complex problems, many AI systems will collaborate with other AI subsystems (such as smart robots or multiagents) and human users. Multiagent systems must have a willingness to continuously learn, review, and adapt their interaction methods throughout an ongoing conversation in order for this form of interaction to occur [2]. Nowadays, Human-Robot collaboration (HRC) is an extremely popular term in the industry. HRC can be described as a situation in which a robot system that has been specifically developed and a human operator work on tasks simultaneously within a collaborative workspace, i.e., where the robot system and a human can do tasks simultaneously or even cooperatively [3]. Collaborative robots (Cobots) are widely used in the manufacturing industry, which are potentially simple tools that can increase productivity without sacrificing the benefits offered by a human-centered system [4]. The variety and amount of robotic applications in manufacturing are constantly expanding, making it crucial to examine the impact of AI on HRC. The goal of using robotics in production has traditionally been to make use of the benefits that robots have over people, such as repeatability, resilience, power, and the capacity to operate in dangerous settings [3]. Most of the time, Robots are trained through various techniques such as machine learning language, reinforcement learning, Simulations, etc. It consumes quite a long period of time. Sometimes, Robots cannot relate to human directions which causes massive losses to industries. As consultants in the high-tech manufacturing industry, we would suggest Cognitive Interaction in Human and Robotic systems as well as AI systems.

1.2 Neuroscience in Industry

Smart Manufacturing has gained end-to-end integration systems with the role of Cyber-Physical Systems (CPS). Every industrial sector is utilizing the best of Artificial Intelligence (AI) and Machine Learning (ML) to centralize data for synchronous exploration. With the time of innovation, the following revolution will be a more interactive connection in human-AI agents that will reintroduce any lost personal imprint in the loop of the industrial process [5]. Neuroscience can directly leads this advanced innovation which will assist in removing a lot of limitations between human and AI agents. Numerous areas, including human performance, safety, and cognitive interactions with AI and robotic systems, have the potential to be revolutionized by the incorporation of neuroscience into the manufacturing industry. Neuroscience basically discusses the nervous system in the human brain. Neurocognition dedicatedly focuses on the human mind which is linked to cognitive functions, and allowed to discuss the ability of thinking and reasoning of human. Worker safety in manufacturing environments can benefit from neurocognition. Researchers can identify cognitive conditions like weariness, tension, or distraction through the analysis of brain activity. These conditions can impair attention and reaction times of employees, which may result in accidents. Neurocognition's approach, Brain-Computer Interface (BCI) provides guidance on how to create secure and comfortable work environments, efficient warning systems, and real-time cognitive monitoring to reduce accidents and enhance employee wellbeing [6]. There are three main categories of Brain-computer interface (BCI) systems, active BCI, reactive BCI, and passive BCI. When a human being can consciously alter their brain activity to highlight neural aspects that will be recognizable following mathematical processing and classification according to the Motor Imagery (MI) paradigm. This phenomenon is known as Active BCI. The Reactive BCI depends on the neurological activity that is often initiated by an external input, primarily visual or auditory, and that elicits brain responses. To assess psychological states like drowsiness, frustration, or even cognitive load, passive BCI employs brain activity that is not intentionally modified by the user [7].

BCI based on electroencephalograms (EEG) has the potential to develop significant and appealing smart systems by smoothly incorporating human perception into the smart manufacturing process. EEG-based BCIs are a rapidly evolving area. Due to aspects including less long-term usage risks (compared to invasive BCIs), price, and portability, non-invasive EEG is suitable for industrial people [5]. Though some invasive BCI practices tend to perform, they are not already used in the practical field. Most improved ones are in trial sessions. Neuralink would be great to shed light on this approach.

Neuralink company, founded by Elon Musk, is dedicated to neuroscience innovation. This company has created a link made of sealed, implanted device that will process and transmit neural signals to control computers or mobile phones from anywhere. The primary objective of this technology is to assist paralyzed individuals in regaining their independence through the use of computers and mobile devices. As a result, these devices are presently being developed so that people will eventually be able to communicate more simply through text or speech synthesis, explore the web for answers, or express their creativity through photography, art, or writing apps. It is believed that this technology has the power to alleviate a variety of neurological conditions, to reestablish sensory and motor function, and ultimately to change the way we relate to one another and perceive our surroundings [8]

1.3. Current State of HRC

Nowadays, Robotic arms and Robots are the most common in the manufacturing industry. repetitive tasks, material handling, assembled tasks, packaging, different types of drilling and welding, etc. are generally assigned to robots. In spite of having such advantages, the most important issue is industrial safety regulations that forbid robots and human operators from working together in the same environment. To overcome these difficulties, AI methodologies have been created and used for HRC [3]. AI, especially Machine Learning (ML) creates a trustworthy environment in industries that assist humans to focus on more creative tasks. Figure 1 depicts some areas where ML is used widely in HRC.

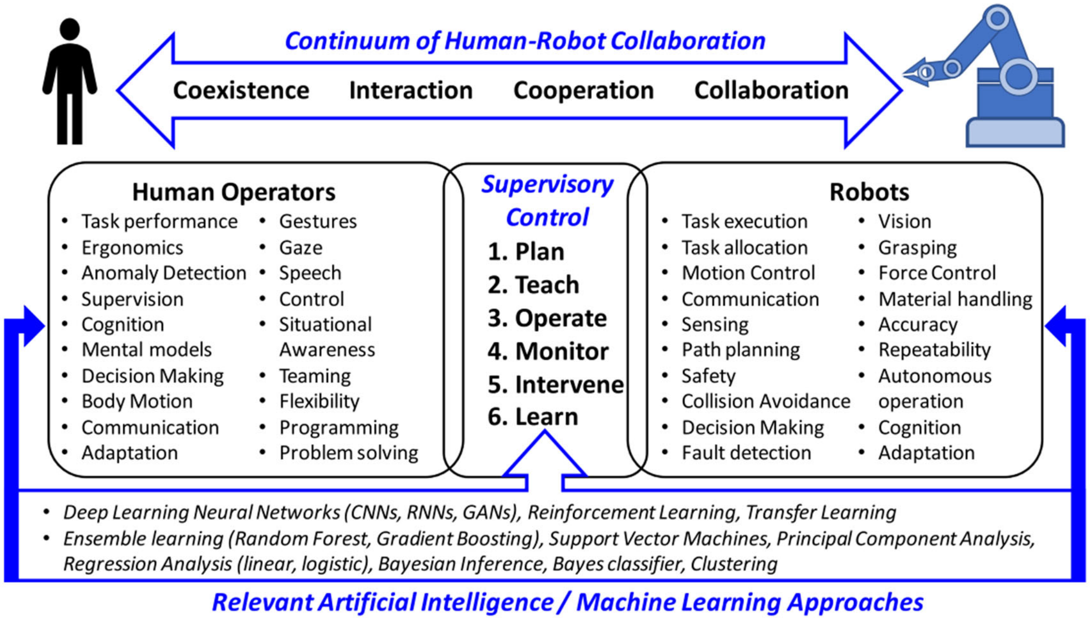

Figure 1: Demonstrative sets of actions, functions, requirements, characteristics, and behaviors for human operators and robots which are candidates for application of AI/ML approaches [3]

Though AI assists and sometimes leads to many functionalities, AI still lacks some features, such as potential decision-making, Category formation & classification, Visual/auditory perception, emotion recognition, Pattern recognition, Continual & meta-learning, and self-adaptation. All of these features indicate cognitive skills which is a hot topic for Human-AI research [2]. Building effective communication, collaboration, adaptability, and most importantly, trust, Cognitive interaction is necessary that can lead to future successful industries.

2. Predicted Improvements

For the improvement of a high-tech global enterprise in 2040, our focus point should be on the implementation of neurocognition in our industry. Our industry needs to utilize cognitive interaction and BCI for the betterment of the industry. This approach will enable the use of the human brain directly with modern machines and will be necessary to become competitive globally.

The primary benefit that can be seen from the implementation of BCI systems in a manufacturing environment is an increase in various productivity benchmarks. Cognitive interaction between humans and robots enables collaboration between them, utilizing their respective advantages. Humans can concentrate on complicated decision-making, problem-solving, and creative jobs, while robots can carry out repetitive operations with high precision and speed. By using BCI, Brain signals can be used by employees to communicate their intentions and instructions to robots, resulting in a faster, more efficient, and natural workflow between the human and AI agent or robot. Improved task integration, increased output, and greater overall performance in industrial processes can all be a result of this collaboration, thus promoting the increase in manufacturing operations' overall productivity.

The current advantage of robots in the industry is that they excel at accomplishing routine jobs precisely and consistently. With the addition of the social interaction that is coordinated using BCI, adaptation and decision-making in robots can be improved [9]. This combination of precision and cognitive skills through BCI allows robots to better understand their surroundings, respond to changing circumstances, and make wise decisions. This results in higher quality control and fewer production process failures in a manufacturing environment. This implementation would also bring benefits to the human worker. BCI systems promote an increase in safety and ergonomics in manufacturing environments due to the no-contact approach taken with the system. Workers are given the opportunity to complete jobs and monitor tasks remotely or from a safer distance, in turn decreasing their exposure to hazardous situations by directing robots through remote brain signals. This method in turn improves workplace safety and reduces the risk of accidents or injuries.

The final benefit we will highlight is the idea that manufacturing operations can take advantage of the adaptive automation made possible by BCI. Robots using this technology can keep track of the goals and cognitive states of human workers and modify their actions accordingly to meet any changes in task priority or instructions. For instance, the robot can autonomously take over specific activities or provide more support to lighten the workload if a person is tired or overworked.

3. Challenges

All of the improvements mentioned above can be seen in successful implications of BCI and AI systems in a manufacturing environment. However, this technology is not viable for large scale use in today’s manufacturing world. With what has already been showcased and research in the implementation of AI systems and neuroscience in industry, a number of challenges present themselves that must be addressed for high-tech enterprises to take full advantage of this technology.

3.1 Challenges for interactive AI system in Industry

1. System-Level Analysis: Due to the uncertain and non-linear dynamical nature of manufacturing systems, as well as the intricate multi-stage processes and dependencies among heterogeneous data, Machine Learning (ML) has seen increasing utilization across all levels of the manufacturing system hierarchy. However, ML is limited at the system level of decision-making. As of right now, there is no single AI tool or group of tools that can combine and handle every performance goal of various control systems [3]. For example, in the field of aviation manufacturing, the Boeing 737 Max provides an illustration of human-AI interaction. The MCAS (Maneuvering Characteristics Augmentation System) system, which was AI-driven and intended to prevent holding up,

was installed on the aircraft. 346 people died as a result of two crashes that took place as a result of the system failing. Investigations showed that the system had been built without sufficient system safety measures and that pilots had not received the necessary instruction on how to handle problems in time.

2. Data Security: AI methods have proven to be effective at properly modeling and optimizing system performance, nearly understanding human movements, identifying and categorizing flaws, and forecasting future machine situations. However, due to security considerations, data gathering, interchange, and accessibility may be prohibited. Moreover, when it is the time for a well-connected system, it is hard to access and interchange in large-scale industry [3].
3. Modeling Material-Processing-Property Relationships: By avoiding the complexity of modeling the entire material-processing-property link, AI approaches present the potential to increase prediction accuracy and productivity in a range of manufacturing processes [3]. Updating parameters from the modeled process is difficult with conventional modeling and control systems since they require a lot of computation. It is typically hard to have a prior understanding of the structure of the process dynamics and the constraints on model uncertainty.
4. Promoting Trust and Ethics in Artificial Intelligence: AI has grown in significance in manufacturing, however, it can be harder for non-experts to comprehend and analyze the results of AI tools and related technical information. This emphasizes how crucial it is for decision-makers who might not be AI professionals to properly evaluate AI analysis. The issue of AI trust will grow more relevant and draw more concentrated study activities as AI research advances. Another important thing is AI systems are generally trained with various algorithms. Sometimes the training data may be biased with societal issues or lack of transparency. These concerns also indicate transparency of data and some ethical questions [3], [7]. There is an example of this kind of failure from TESLA. In the vehicle manufacturing sector, the Tesla Autopilot system is an illustration of a Human-AI interaction. The technology, however, has been a part of a number of mishaps, some of which have been fatal. For instance, a Tesla Model X that was utilizing Autopilot in 2018 smashed into a concrete barrier, killing the driver. Investigations showed that the driver had disregarded the system's repeated requests for him or her to take the wheel.

`3.2 Challenges for Neurocognition Approach in Industry

1. Data Security and Device Control: Industrial Brain-Computer Interface (BCI) has to assure data security and confidentiality, store and process personal data locally, and can actually improve working conditions and/or safety. Active and reactive non-invasive BCI for device control are still insufficiently developed for agents to utilize and adopt. Training sessions that are frequent and difficult can be physically, emotionally, and financially taxing on the user, which can cause frustration [7].

2. Training Cost for user experience: Implementation of neuroscience, as Brain-Computer Interface (BCI) solutions must be non-invasive, comfortable to wear, portable and not bulky, non-tiring, multitasking-compatible, and inexpensive in terms of training time and resources. It will require time-to-time feedback from users on whether it fits in its quality. Passive BCIs are more suited to the criteria of portability, non-fatigability, and multitasking, nonetheless, the training cost is particularly important in active and reactive paradigms [7].
3. Technical Specifications for Industry: For absolute reliability, reactivity in terms of response time, and flexibility to respond to context and individual variances, BCI technical specificities must be considered. Compared to active and passive paradigms, reactive BCI and SSVEP-based BCI appear to be more reliable and flexible. Active paradigms have a lesser level of flexibility and a higher percentage of illiteracy. The effectiveness of the signal that is acquired and the applicability of the AI algorithms determine reliability. BCI must be flexible and adaptable for large-scale deployment in order to be usable and similarly dependable for a large number of users [7].

4. Advanced Preparations

4.1 Skill Reusability

The notions of transfer learning, multi-task learning, and learning-to-learn are all strongly related to the idea that learning a new activity can be improved by prior experience with other similar tasks. Future learning approaches could assist in developing collaborative robots that can conduct a wide range of activities without specialization training. By applying knowledge to different tasks and circumstances, skill reusability is an open problem that offers many options for streamlining and improving robot programming for collaborative robots [10].

4.2 Cloud System

Data is now incredibly expensive for all industries. The data is more important than anything else when discussing a major industry or a worldwide chain sector. For data, collection, storage, and security are absolutely essential. In this case, the Cloud space will be perfect choice for real-time data, collaboration and sharing data, scalability, and computational capacity. By effectively storing data, processing brain signals, and encouraging cooperation and innovation in the field, cloud resources enable researchers and practitioners to fully realize the potential of BCI. More advancement of technology will create two way (Human Brain to Robot, Robot to Human Brain simultaneously) learning system through cloud space and EEG. This kind of advancement will open new era of solving any complicated problem smoothly and precisely [11].

As the interaction is between human and AI systems, Affectiva can be considered a good example. The AI system of Affectiva claims that it can identify all aspects of human activity, including sophisticated human cognitive states, behaviors, interactions, and human-usable items. Deep learning, computer vision, voice analytics, and a lot of data gathered in real-world situations are used to build this AI system. It is an emerging technology in Human-AI cognitive interaction. The system provides a lot of importance on Human perception AI that will occupy to track all kinds of emotions. The advancement of this technology can predictably lead to the next-generation manufacturing process [12].

4.3 Worker Training

Regardless of the level of education obtained prior to employment, for each industry, it is necessary for new workers to undergo training. Each process unique to the product or facility requires a unique training module or method, which is utilized to familiarize workers with tools and processes used in their respective roles. BCI is no exception to this concept. The implementation of a training or onboarding program to familiarize workers with BCI would prove greatly beneficial to the company. It has already been shown that AI systems can be incorporated into training systems via a VR environment to improve the measured performance on a given task [13], and we can expect to see similar results when incorporating BCI methodologies into industry training programs.

5. Conclusion

In conclusion, the combination of Brain-Computer Interface (BCI) technology with Human-AI Cognitive Interaction has the potential to fundamentally change how people and computers interact and collaborate. BCI can make it possible for the human brain and AI systems to communicate with each other directly and naturally, facilitating smooth information exchange and increasing cognitive interaction. Humans may control and communicate with machines using their thoughts, intents, and neurological impulses owing to the unity of BCI and AI in the future. Industries can gain from increased productivity, increased safety, and more effective decision-making processes by utilizing BCI. However, overcoming technological obstacles, maintaining data privacy and security, and fostering user acceptability through efficient user training and usability are all necessary for the successful realization of human-AI cognitive interaction with BCI. The future is promising as a result of continued developments in BCI technology and AI algorithms. However, it is essential to continue research and development efforts to unlock the full potential of BCI in human-AI cognitive interaction and optimization for a wide range of applications across industries.

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